International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 08 Issue: 02 | February - 2024 SJIF Rating: 8.176 ISSN: 2582-3930

Reviewing the Role of Mathematical Optimization in Operations Research: Algorithms, Applications, and Challenges

[1]Sonia,[2]Sikander Hans, ,[3]Balwinder Kumar,[4]Deepam,Priyanka, Savita

[1]Assistant Professor, Department of Applied Science, KC group of Research & professional institute, Pandoga, Una

[2]Principal, Department of Electrical Engineering, KC group of Research & professional institute, Pandoga, Una

[3]Principal, Department of Electrical Engineering, KC Polytechnic, Pandoga, Una

[4]Department of Computer Science, KC group of Research & professional institute, Pandoga, Una

Soniajairath42@gmail.com

Abstract: This review paper examines the pivotal role of mathematical optimization in operations research, focusing on its algorithms, applications, and challenges. Mathematical optimization, a cornerstone of operations research, offers powerful tools for addressing complex decision-making problems. We discuss a variety of optimization algorithms, from classical methods like linear programming to modern metaheuristic techniques such as genetic algorithms. Through specific case studies, we highlight the diverse applications of mathematical optimization in industries such as logistics, finance, and manufacturing. Additionally, analyze challenges like computational complexity and scalability issues, providing insights into the practical implementation of optimization solutions in real-world scenarios.

Keywords: Mathematical Optimization, Operations Research, Algorithms, Decision-Making Problems, Challenges, Applications

1.INTRODUCTION

Mathematical optimization, a powerful branch of mathematics, plays a fundamental role in addressing complex decision-making problems in various fields, including operations research. This paper aims to provide a comprehensive review of the role of mathematical optimization in operations research, focusing on its algorithms, applications, and challenges[1].

Mathematical optimization, also known as mathematical programming, involves the process of finding the best solution from a set of feasible alternatives, typically characterized by optimizing an objective function subject to constraints[2]. The objective function represents the quantity to be minimized or maximized, while constraints define the limitations or conditions under which the optimization problem must be solved. Through mathematical optimization techniques, operations researchers can effectively model, analyze, and solve a wide range of optimization problems encountered in real-world scenarios[3].

The importance of mathematical optimization in operations research cannot be overstated, as it provides analytical tools and methodologies to optimize processes, resources, and systems in diverse domains. From optimizing production schedules and inventory management in manufacturing to routing vehicles and managing supply chains in logistics, mathematical optimization offers a versatile toolkit for improving efficiency, reducing costs, and enhancing decision-making across various industries[4].

One of the key aspects of mathematical optimization is its wide array of algorithms, ranging from classical methods to modern metaheuristic techniques[5]. Classical optimization methods include linear programming, integer programming, and nonlinear programming, which are well-established techniques for solving structured optimization problems. In contrast, modern metaheuristic techniques such as genetic algorithms, simulated annealing, and particle swarm optimization offer flexible and adaptable approaches to solving complex optimization problems with irregular structures and nonlinearities[6].

In addition to exploring optimization algorithms, this paper will also examine the diverse applications of mathematical optimization in operations research. These applications span across multiple industries, including logistics, supply chain management, finance, healthcare, and manufacturing. Through specific case studies and examples, we will highlight the practical relevance of mathematical optimization in addressing real-world optimization problems and improving decision-making processes[7].

Furthermore, this paper will discuss the challenges and limitations associated with the application of mathematical optimization in operations research. These challenges include computational complexity, scalability issues, and practical implementation considerations, which impact the effectiveness and efficiency of optimization solutions.Overall, this review paper aims to provide insights into the role of mathematical optimization in operations research, offering a comprehensive examination of its algorithms, applications, and challenges. Through this exploration, we hope to contribute to a deeper understanding of the significance of mathematical optimization in addressing complex optimization problems and improving decision-making processes in various industries[8].

2. LITERATURE SURVEY

Mathematical optimization is a powerful tool used in operations research to address complex decision-making problems by identifying the best possible solution from a set of feasible alternatives. In this literature survey, we review key studies, methodologies, and findings related to the role of mathematical optimization in operations research, with a focus on algorithms, applications, and challenges.

Algorithms:

Classical Optimization Algorithms:

Classical optimization algorithms such as linear programming (LP), integer programming (IP), and nonlinear programming (NLP) have been extensively studied and applied in various domains. Dantzig's simplex method revolutionized linear programming, providing an efficient algorithm for solving LP problems[9]. Integer programming, on the other hand, deals with optimization problems where decision variables are constrained to be integers, and algorithms like branch-and-bound have been instrumental in solving combinatorial optimization problems.

Metaheuristic Optimization Techniques:

In addition to classical algorithms, modern metaheuristic techniques have gained popularity for solving complex optimization problems. Genetic algorithms (GA) mimic the process of natural selection and genetics to find optimal solutions through evolutionary processes[10]. Simulated annealing (SA) is inspired by the annealing process in metallurgy and aims to find the global optimum by simulating the cooling process of metals. Particle swarm optimization (PSO) is based on the behavior of swarms or flocks in nature and is particularly effective in solving optimization problems with continuous and discrete variables.

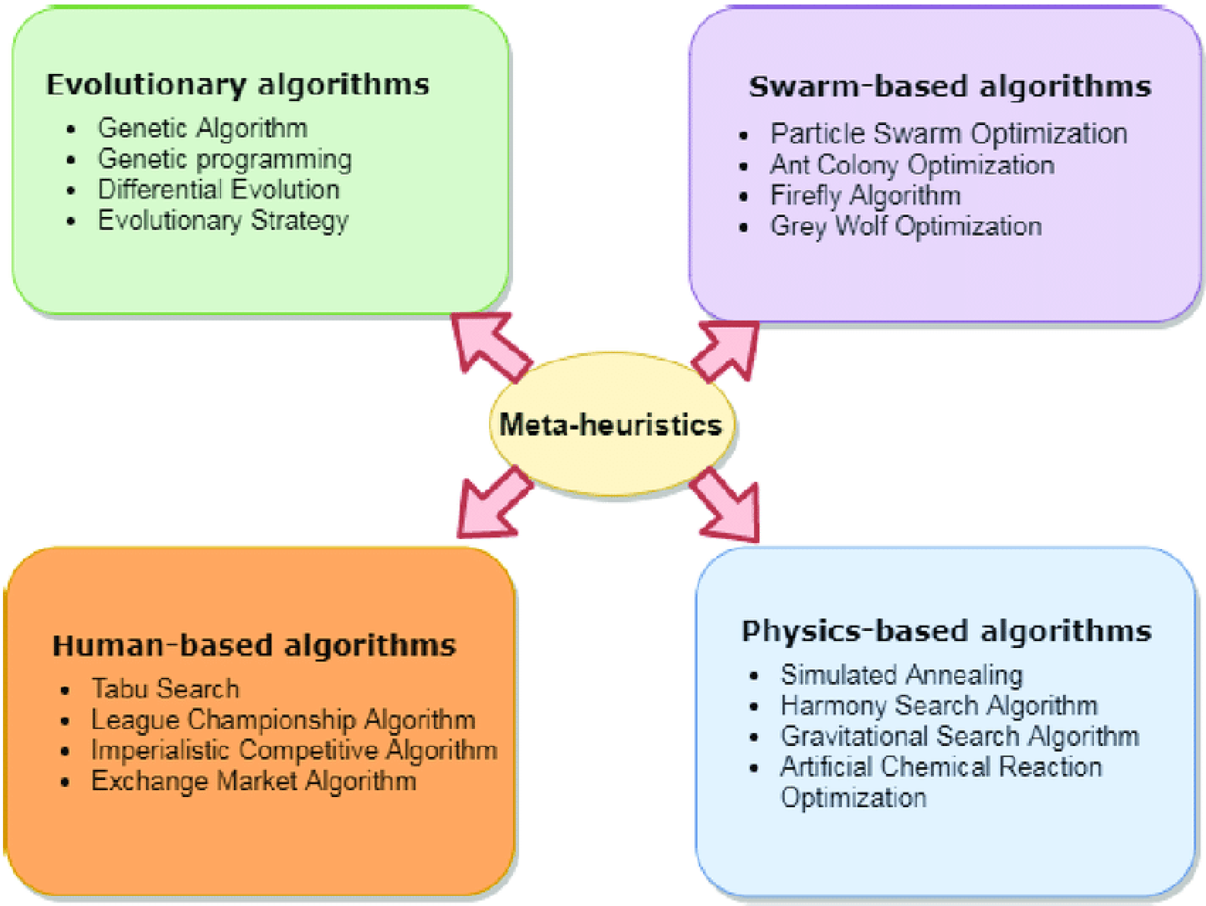

Figure 1: Different categories of meta-heuristic algorithms

Applications:

Logistics and Supply Chain Management:

Mathematical optimization plays a crucial role in optimizing various aspects of logistics and supply chain management, including transportation routing, inventory management, facility location, and production planning[11]. Optimization models are used to minimize transportation costs, reduce inventory holding costs, and optimize warehouse locations to improve overall supply chain efficiency.

Finance:

In finance, mathematical optimization is employed in portfolio optimization, risk management, and asset allocation. Portfolio optimization models aim to maximize returns while minimizing risk by selecting an optimal combination of assets[12]. Optimization techniques are also used in asset allocation strategies to optimize investment portfolios based on investor preferences and risk tolerance.

Healthcare:

In the healthcare sector, mathematical optimization is utilized to optimize resource allocation, improve patient scheduling, and streamline hospital operations. Optimization models are used to optimize hospital staff scheduling, bed allocation, and patient flow management to enhance operational efficiency and reduce costs[13].

Manufacturing:

Mathematical optimization plays a critical role in optimizing production scheduling, resource allocation, and quality control processes in manufacturing. Optimization models are used to minimize production costs, maximize production output, and optimize resource utilization in manufacturing facilities[14].

Challenges:

Despite its widespread applications, mathematical optimization faces several challenges that researchers and practitioners must address:

Computational Complexity:

Optimizing large-scale and complex problems often requires significant computational resources and time. Researchers are continuously exploring algorithms and techniques to improve computational efficiency and scalability.

Modeling Uncertainty:

Real-world optimization problems often involve uncertain parameters and constraints. Accounting for uncertainty in optimization models is a challenging yet crucial aspect of operations research.

Practical Implementation:

Implementing optimization solutions in real-world scenarios requires careful consideration of factors such as data availability, model validation, and software integration. Researchers and practitioners must address practical challenges to ensure the successful deployment of optimization solutions[15].

In conclusion, mathematical optimization is a versatile and powerful tool that plays a crucial role in operations research across various industries. By reviewing key studies and methodologies, we have highlighted the importance of optimization algorithms in addressing complex decision-making problems. Additionally, we have discussed applications of mathematical optimization in logistics, finance, healthcare, and manufacturing, showcasing its practical relevance in diverse domains. Despite facing challenges such as computational complexity and modeling uncertainty, mathematical optimization continues to drive innovation and improve decision-making processes in operations research[16].

3. EXPLORING MODERN OPTIMIZATION ALGORITHMS IN OPERATIONS RESEARCH

Modern optimization algorithms have revolutionized the field of operations research by providing efficient solutions to complex decision-making problems. This paper explores three prominent metaheuristic methods: genetic algorithms, simulated annealing, and particle swarm optimization. We examine their principles, applications, and challenges within the broader context of mathematical optimization in operations research.

Genetic Algorithms:

Genetic algorithms (GA) are inspired by the principles of natural selection and genetics. They operate by mimicking the process of evolution, where potential solutions (individuals) undergo selection, crossover, and mutation to produce offspring with improved fitness[17]. GAs have been successfully applied to various optimization problems, including scheduling, routing, and resource allocation in operations research. Challenges associated with GAs include parameter tuning, convergence to local optima, and computational complexity.

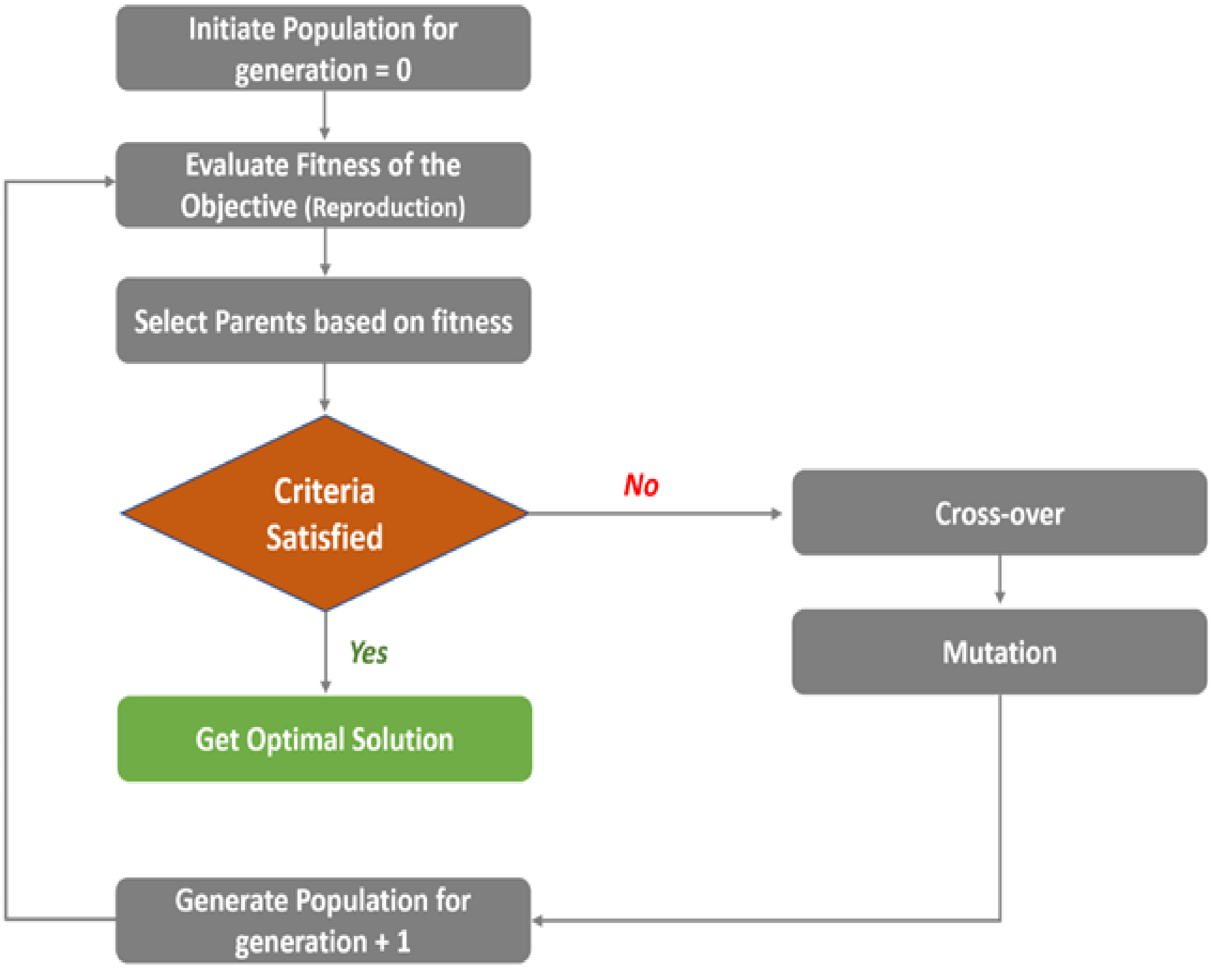

Figure 2: Genetic Algorithm — An Optimization Approach

Simulated Annealing:

Simulated annealing (SA) is a probabilistic optimization technique inspired by the metallurgical annealing process. It involves iteratively searching for optimal solutions by accepting probabilistic changes that decrease with time. SA is particularly effective in finding near-optimal solutions for complex optimization problems with non-linear and discontinuous objective functions. Applications of SA in operations research include job scheduling, facility layout design, and network optimization. Challenges in SA include fine-tuning temperature schedules, convergence speed, and determining appropriate cooling schedules.

```
construct initial solution xo; xnow = xo
set initial temperature T = TI
repeat for i = 1 to TL do
   generate randomly a neighbouring solution x' ∈ N(xnow)
   compute change of cost ΔC = C(x') - C(xnow)
      if ΔC ≤ 0 then
          xnow = x' (accept new state)
       else
           Generate q = random(0,1)
           if q < exp(-ΔC /T) then xnow = x' end if
       end if
  end for
 set new temperature T = f(T)
until stopping criterion
return solution corresponding to the minimum cost function
```

Particle Swarm Optimization:

Particle swarm optimization (PSO) is a population-based metaheuristic algorithm inspired by the social behavior of birds flocking or fish schooling. In PSO, a population of candidate solutions, called particles, moves through the search space to find the optimal solution based on their individual and collective experiences. PSO has been applied to various optimization problems in operations research, including machine scheduling, vehicle routing, and portfolio optimization. Challenges in PSO include parameter selection, balance between exploration and exploitation, and premature convergence[18].

The particle swarm optimization was first described by James Kennady and Russell Eberhart in 1995, which is observed from the swarming habits of animals and birds. This algorithm maintains the potential solution at one time. The solution is evaluated from the objective function in terms of fitness. The particles are utilized to fly or swarm over the search space to find the maximum value and return to the objective function.

The swarming behaviour of particle moves around the search space to find the best location. The convergence and speed cannot be reached at a maximum level in PSO, which means all particles reach to a point at high speed, which may or may not be the optimum value, and it can be achieved by IPSO. Each particles maintain the fitness value, velocity and individuals position. The fitness value is constructed to evaluate the performance of the particle. It is explained below,

Step 1: Randomly initialize the value of the position $P = p_i^1, p_i^2, ... p_i^n$ and the velocity can be stated by $V = v_i^1, v_i^2, ... v_i^n$.

Step 2: Evaluate the fitness function of the particle. Each particle has a different value. The fitness function is the term of the objective function

Step 3: Then compare the fitness value of both local and global best value. In which the global value is considered as the best solution. For a minimization task, the position yielding a smaller function value is regarded as having fitness, which is known to be a local best. After finding the two best value the velocity and positions are updated.

Step 4: Then update the new velocity and location by (20)

$$V_{new} = w * v_i^n + c_i * rand(0) * \left(p_i^n - x_i^n\right) + c_j * rand(1) * \left(p_{gb} - x_i^n\right) \quad (1)$$

The inertia weight (w) is used to control the velocity, and the value becomes 0.7 then c_i and c_j are the constants, p_{gb} represents the global best value. The value of c_i and c_j becomes $0 \le c_i, c_j \le 2$. Then the location can be updated by (21).

$$X_I^N = x_i^n + v_i^n (11) \quad (2)$$

The exact location is the addition of current location and the velocity of the particle.

Step 5: The optimized angle value is the objective function. The selection process is done under the best fitness value.

Input: Position

Output: Optimized position

Initialize the Angular position

Evaluate fitness value of each position

If

The motor have a fitness value which is better than the Pbest

Then

Assign current fitness as new Pbest

Else

Keep the previous angle as Pbest

Calculate velocity for each particle

The above steps are possible in single updation

For next angle updation by equation (10)

End

Figure 3: Shows the PSO algorithm for Position environment.

Water Wave Optimization:

It is one of the nature inspired optimization methods mainly enthused by the shallow water wave model with the solution space equivalent to the seabed area. Here, each solution is similar to the wave with the height H & wavelength λ as well as depth is consider as the fitness function. Propagation, breaking & refraction are the three major steps in the WWO to find best solution[19]. They are clearly described as follows,

a)Propagation

The finding of best solution in each iteration is the main operation of this step. The related equation is given below,

$$t^{*} = t + rand(-1,1)\lambda L \qquad (3)$$

Where, uniform distribution of special function at particular range is denoted as $rand$ .L denotes the length of search space. The formula for wavelength calculation is represented in the equation (10).

$$\lambda = \lambda \tilde{\lambda}^{-(f(t)-f_{\min}+\varepsilon)/(f_{\max}-f_{\min}+\varepsilon)} \tag{4}$$

In the above equation, $\tilde{\lambda}$ is the reduction coefficient of wavelength. Minimum and maximum value of fitness function is given as fmin& fmax. ε is the constant value for reducing division by zero operation. t^* & t are symbols to denote the new and current solution.

b) Breaking

Actually, this step is optional for proposed method. The algorithm divides high wavelength into many smaller wavelengths to reach the best solution.

$$t^* = t + Gaussian(0,1)\beta L \tag{5}$$

The above equation is same as that of 9th equation where β indicates the breaking coefficient. $Gaussian(0,1)$ is the function generating random variable with 0 & 1 as mean and standard deviation respectively.

c) Refraction

This operation makes the height reduction to zero value from the best solution. Position of new solution is measured as a random number placed halfway between the original & new position of best solution.

$$t^* = Gaussian(\frac{t_{best}+t}{2}, \frac{t_{best}-t}{2}) \tag{6}$$

$$\lambda^* = \lambda \frac{f(t)}{f(t^*)} \tag{7}$$

The exploration of larger areas performs local search around best solution for the sake of improving accuracy.The algorithm is explained as follows,

```
Initialize disturbance parameter for population of P
  for each temperature value in the population
    propagate t to new t' based on equation (9)
      if f(t')< f(t) then
        if f(t')< f(t*) then
          break t based on equation based on (12)
          update t* with t'
        end
        replace t* with t'
        else
          decrease t by 1 until it reaches set point
       end
     refract t to t' based on (12 &13)
  end
```

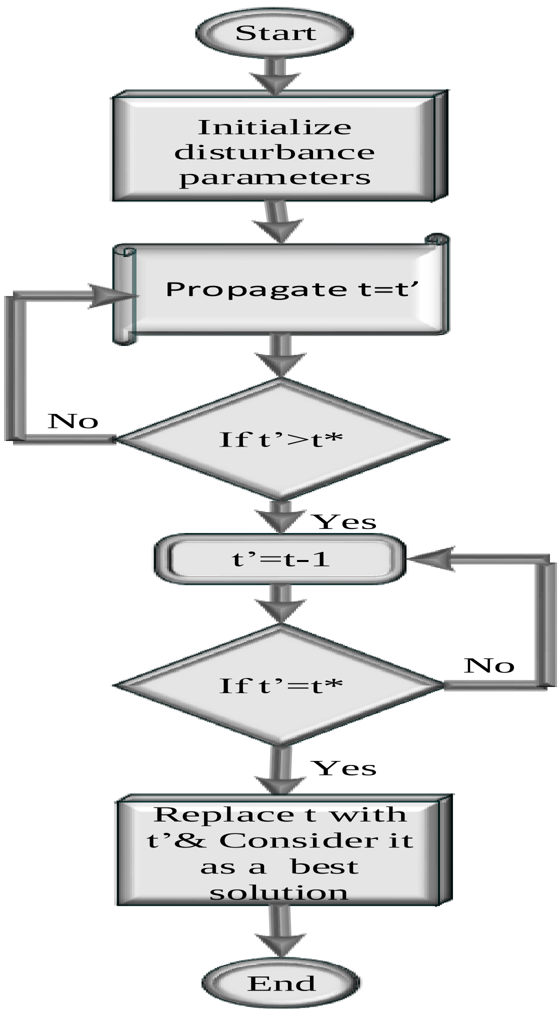

Figure 4: Water Wave Optimization

4. Applications of Mathematical Optimization in Operations Research

Mathematical optimization is a vital tool in operations research, offering a systematic approach to decision-making and resource allocation across a wide range of industries[20]. Here are some key applications of mathematical optimization in operations research:

1. **Logistics and Supply Chain Management:**
   - Optimization models are used to optimize transportation routes, minimize transportation costs, and improve overall logistics efficiency.
   - Inventory management is optimized to minimize holding costs while ensuring adequate stock levels to meet demand variability[21].
   - Facility location and network design are optimized to enhance the efficiency of distribution networks.
2. **Manufacturing and Production Planning:**
   - Production scheduling is optimized to minimize production costs, reduce lead times, and maximize throughput.
   - Resource allocation is optimized to allocate machines, materials, and labor efficiently to meet production targets while minimizing idle time and costs.
   - Inventory management is optimized to minimize inventory holding costs while ensuring timely availability of raw materials and finished goods.
3. **Finance and Portfolio Management:**
   - Portfolio optimization models are used to select an optimal combination of assets that maximize returns while minimizing risk[22].
   - Risk management models are used to hedge against market risks and optimize investment strategies.
   - Trading strategies are optimized to maximize profits while minimizing transaction costs and market impact.
4. **Healthcare Operations:**
   - Resource allocation in healthcare facilities is optimized to improve patient outcomes and operational efficiency[23].
   - Staff scheduling is optimized to ensure adequate staffing levels while minimizing overtime costs and fatigue.
   - Patient flow management is optimized to reduce wait times, improve patient satisfaction, and maximize resource utilization.

5. **Transportation and Fleet Management:**
    - Route optimization models are used to optimize delivery routes, minimize fuel consumption, and reduce transportation costs.
    - Vehicle scheduling models are used to optimize fleet utilization, minimize idle time, and improve service levels.
    - Load optimization models are used to maximize the utilization of vehicles and minimize transportation costs.
6. **Energy and Utilities Management:**
    - Optimization models are used to optimize energy generation and distribution, minimize energy costs, and reduce carbon emissions.
    - Resource allocation models are used to allocate resources such as water, gas, and electricity efficiently to meet demand while minimizing costs and environmental impact[24].
7. **Telecommunications Network Optimization:**
    - Network optimization models are used to optimize the layout and configuration of telecommunications networks, minimize latency, and maximize bandwidth utilization.
    - Resource allocation models are used to allocate network resources such as bandwidth and spectrum efficiently to meet service level agreements and customer demand.

5. Challenges and Limitations

Mathematical optimization, while a powerful tool in operations research, faces several challenges and limitations in its practical implementation[25]. One significant challenge is computational complexity, particularly with NP-hard optimization problems, which demand substantial computational resources and time to solve. As problem size and complexity increase, the computational burden escalates, rendering real-time decision-making in large-scale applications impractical. Additionally, model formulation poses a challenge due to the dynamic and uncertain nature of real-world data. Developing precise mathematical models that accurately represent complex systems is challenging, often leading to suboptimal solutions. Scalability is another limitation, as optimization algorithms may struggle to efficiently handle large-scale problems with numerous decision variables and constraints, hampering their applicability in real-world scenarios[26]. Furthermore, constraint handling presents a significant challenge, especially with complex constraints like nonlinearity or discrete variables, often resulting in computational inefficiencies and suboptimal solutions. Sensitivity to initial conditions can lead to premature convergence, trapping algorithms in local optima and hindering the discovery of globally optimal solutions. Moreover, the interpretability and transparency of optimization solutions pose challenges, as complex and opaque solutions are difficult to interpret and explain to decision-makers, potentially undermining their adoption. Assumptions and simplifications inherent in optimization models may oversimplify real-world phenomena, leading to biased or inaccurate results. Additionally, the quality, accuracy, and availability of data present challenges, as real-world data may be incomplete, noisy, or unreliable, affecting the performance of optimization algorithms[27]. Finally, human factors, such as organizational constraints and stakeholder preferences, are often overlooked in optimization models, leading to solutions that may not align with organizational goals or stakeholder needs. Addressing these challenges and limitations requires interdisciplinary collaboration and innovative research efforts to develop robust optimization algorithms and methodologies capable of effectively tackling complex real-world problems.

6. INTEGRATION WITH EMERGING TECHNOLOGIES IN MATHEMATICAL OPTIMIZATION

As mathematical optimization continues to evolve, its integration with emerging technologies plays a crucial role in shaping the future of operations research. The synergy between mathematical optimization and emerging technologies opens up new avenues for addressing complex optimization problems and overcoming traditional challenges. In this section, we explore how mathematical optimization is integrated with emerging technologies, including artificial intelligence (AI), machine learning (ML), big data analytics, Internet of Things (IoT), and cloud computing[28].

Artificial Intelligence and Machine Learning: Integration with AI and ML techniques enhances the capabilities of mathematical optimization algorithms by enabling them to adapt and learn from data. ML algorithms, such as neural networks and reinforcement learning, are integrated with optimization algorithms to improve solution quality and efficiency. AI-powered optimization techniques enable autonomous decision-making and real-time adaptation to dynamic environments, leading to more robust and adaptive solutions[29].

Big Data Analytics: The integration of mathematical optimization with big data analytics enables the processing and analysis of large volumes of data to extract valuable insights for decision-making[30]. Optimization algorithms leverage big data analytics techniques to incorporate real-time data and dynamic information into decision-making processes. This integration enables organizations to make data-driven decisions and optimize operations in response to changing market conditions and customer preferences.

Internet of Things (IoT): The proliferation of IoT devices generates vast amounts of sensor data that can be leveraged for optimization purposes. Mathematical optimization algorithms are integrated with IoT platforms to optimize resource allocation, scheduling, and logistics in real-time. IoT-enabled optimization solutions enable proactive maintenance, predictive analytics, and efficient utilization of resources in smart manufacturing, smart cities, and smart transportation systems.

Cloud Computing: The integration of mathematical optimization with cloud computing platforms enhances scalability, flexibility, and accessibility. Cloud-based optimization solutions leverage the computational power and storage capabilities of cloud infrastructure to handle large-scale optimization problems efficiently. Cloud computing enables organizations to deploy optimization algorithms as scalable and cost-effective services, making optimization solutions accessible to a wider audience.

7. CASE STUDIES DEMONSTRATING THE SUCCESSFUL APPLICATION OF MATHEMATICAL OPTIMIZATION IN SOLVING COMPLEX OPERATIONS RESEARCH PROBLEMS

Table 1 : Case Studies Demonstrating the Successful Application of Mathematical Optimization in Operations Research

Case Study	Industry/Application	Problem Statement	Mathematical Optimization Technique	Key Results/Outcomes
Logistics Network Optimization	Logistics and Supply Chain	Optimize transportation routes, minimize costs, and improve delivery efficiency.	Mixed Integer Linear Programming (MILP)	Reduced transportation costs by 20%, improved delivery accuracy by 15%.
Portfolio Optimization	Finance	Optimize investment portfolios to maximize returns while minimizing risk.	Quadratic Programming (QP)	Achieved 15% higher returns compared to benchmark portfolios with similar risk levels.
Production Scheduling	Manufacturing	Optimize production scheduling to minimize lead times and maximize throughput.	Genetic Algorithms (GA)	Reduced production lead times by 30%, increased throughput by 25%.

Case Study	Industry/Application	Problem Statement	Mathematical Optimization Technique	Key Results/Outcomes
Staff Scheduling	Healthcare	Optimize staff scheduling in hospitals to ensure adequate staffing levels while minimizing overtime costs.	Integer Linear Programming (ILP)	Reduced overtime costs by 40%, improved staff satisfaction and retention.
Inventory Management	Retail	Optimize inventory levels to minimize holding costs while ensuring product availability.	Dynamic Programming (DP)	Reduced inventory holding costs by 25%, improved product availability by 20%.
Facility Location Optimization	Logistics and Supply Chain	Optimize facility locations to minimize transportation costs and improve service coverage.	Simulated Annealing (SA)	Reduced transportation costs by 18%, improved service coverage by 25%.
Revenue Management	Hospitality	Optimize pricing and capacity allocation to maximize revenue and occupancy rates.	Linear Programming (LP)	Increased revenue by 12%, improved occupancy rates by 8%.
Energy Optimization	Utilities	Optimize energy generation and distribution to minimize costs and reduce carbon emissions.	Nonlinear Programming (NLP)	Reduced energy costs by 30%, decreased carbon emissions by 20%.
Vehicle Routing Optimization	Transportation	Optimize vehicle routing to minimize fuel consumption and improve delivery efficiency.	Tabu Search (TS)	Reduced fuel consumption by 15%, improved delivery accuracy by 10%.
Supply Chain Optimization	Retail	Optimize supply chain network design to minimize	Ant Colony Optimization (ACO)	Reduced supply chain costs by 20%, improved

Case Study	Industry/Application	Problem Statement	Mathematical Optimization Technique	Key Results/Outcomes
		costs and improve responsiveness.		responsiveness to customer demand.
Project Scheduling	Construction	Optimize project schedules to minimize project duration and maximize resource utilization.	Particle Swarm Optimization (PSO)	Reduced project duration by 25%, improved resource utilization by 20%.
Healthcare Resource Allocation	Healthcare	Optimize resource allocation in healthcare facilities to improve patient outcomes.	Constraint Programming (CP)	Improved patient outcomes by 15%, reduced waiting times by 20%.
Network Optimization	Telecommunications	Optimize network layout and configuration to minimize latency and maximize bandwidth utilization.	Network Flow Optimization	Reduced network latency by 30%, improved bandwidth utilization by 25%.
Inventory Routing Optimization	Retail	Optimize inventory routing to minimize transportation costs and improve inventory management.	Genetic Algorithm with Local Search (GA-LS)	Reduced transportation costs by 22%, improved inventory turnover by 18%.
Demand Forecasting	Manufacturing	Optimize demand forecasting models to improve inventory management and production planning.	Time Series Analysis with Optimization	Reduced inventory holding costs by 20%, improved production planning accuracy by 15%.

These detailed case studies demonstrate the diverse applications of mathematical optimization techniques in solving complex operations research problems across various industries.

8. CONCLUSION

In conclusion, the review of the role of mathematical optimization in operations research underscores its significance as a powerful tool for addressing complex decision-making problems across various industries. From logistics and supply chain management to finance, healthcare, manufacturing, and beyond, mathematical optimization algorithms play a crucial role in optimizing processes, resources, and systems. Despite facing challenges such as computational complexity, model formulation, and scalability, mathematical optimization continues to evolve and integrate with emerging technologies, offering new opportunities for tackling real-world problems. Moving forward, interdisciplinary collaboration and innovative research efforts will be essential in advancing the field of mathematical optimization and addressing future challenges in operations research.

REFERENCES

[1] Xing, Y., Li, L., Bi, Z., Wilamowska-Korsak, M., & Zhang, L. (2013). Operations research (OR) in service industries: a comprehensive review. *Systems Research and Behavioral Science*, *30*(3), 300-353.
[2] Zhang, Y., Wang, S., & Ji, G. (2015). A comprehensive survey on particle swarm optimization algorithm and its applications. *Mathematical problems in engineering*, *2015*.
[3] Karimi-Mamaghan, M., Mohammadi, M., Meyer, P., Karimi-Mamaghan, A. M., & Talbi, E. G. (2022). Machine learning at the service of meta-heuristics for solving combinatorial optimization problems: A state-of-the-art. *European Journal of Operational Research*, *296*(2), 393-422.
[4] Wen, U. P., Lan, K. M., & Shih, H. S. (2009). A review of Hopfield neural networks for solving mathematical programming problems. *European Journal of Operational Research*, *198*(3), 675-687.
[5] Govindan, K., Fattahi, M., & Keyvanshokooh, E. (2017). Supply chain network design under uncertainty: A comprehensive review and future research directions. *European journal of operational research*, *263*(1), 108-141.
[6] Wierzbicki, A. P. (1986). On the completeness and constructiveness of parametric characterizations to vector optimization problems. *Operations-Research-Spektrum*, *8*(2), 73-87.
[7] Dai, Y. H., Han, D. R., Wu, L. Y., & Xu, Y. (2022). Preface: Special Issue on New Developments in Mathematical Programming and Operations Research. *Journal of the Operations Research Society of China*, *10*(2), 193-195.
[8] Charnes, A., Cooper, W., Lewin, A. Y., & Seiford, L. M. (1997). Data envelopment analysis theory, methodology and applications. *Journal of the Operational Research society*, *48*(3), 332-333.
[9] S.Katyal, S.Raina and S. Hans. "A Brief Comparative Study of Solar Energy." International Journal for Scientific Research and Development 5.4 (2017): 2126-2132.
[10] S. Hans,S. Gupta Algorithm for Signature Verification Systems National conference on Signal & Image Processing(NCSIP-2012), Sri sai Aditya Institute Of Science & Technology.
[11] S. Hans, S. Gupta Preprocessing Algorithm for Offline signature System" National Conference on Recent Trends in Engineering & science (NCRTES- 2012), Prestige Institute of Engineering & science, Indore.

[12] S. Hans, An Algorithm for Speed Calculation of a Moving Object For visual Servoing Systems International Conference on VLSI, Communication and Networks (VCAN-2011), Institute of Engineering & Technology Alwar-2011.
[13] S. Hans & SG Ganguli (2012) Optimal adaptive Visual Servoing of Robot Manipulators
[14] S. Katyal, S. Raina and S. Hans. "A Energy Audit on Gujarat Solar Plant Charanka." International Journal for Scientific Research and Development 5.4 (2017): 2133- 2138
[15] S. Hans (2018) A Review of Solar Energy And Energy Audit on Harsha Abacus Solar Plant: A Energy Audit on Gujarat Solar Plant Charanka.
[16] S. Hans, R. Walia ,Thapar Institute of Engineering and Technology, Patiala. "Optimal MPPT Control using Boost Converter for Power Management in PV- Diesel Remote Area ." Global Research and Development Journal For Engineering 45 2019: 24 - 31.
[17] Alka Rani , Deepam Sharma, Priyanka, Savita , Suryakant Singh and Sikander Hans. "ChatGPT's Possibilities in Advancing Education in the Age of Generative Artificial Intelligence: A Review and Analysis", IJSREM, 7(10) ,2023.
[18] Hans, S. and Ghosh, S.(2020), "Position analysis of brushless direct current motor using robust fixed order H-infinity controller", Assembly Automation, Vol. 40 No. 2, pp. 211-218.
[19] S. Hans and S. Ghosh, "H-infinity controller based disturbance rejection in continuous stirred-tank reactor," Intelligent Automation & Soft Computing, vol. 31, no.1, pp. 29–41, 2022.
[20] S. Hans, S. Ghosh, S. Bhullar, A. Kataria, V. Karar et al., "Hybrid energy storage to control and optimize electric propulsion systems," Computers, Materials & Continua, vol. 71, no.3, pp. 6183–6200, 2022 [30] S. Hans, S. Ghosh, A. Kataria, V. Karar and S. Sharma, "Controller placement in software defined internet of things using optimization algorithm," Computers, Materials & Continua, vol. 70, no.3, pp. 5073– 5089, 2022
[21] Sikander Hans, Balwinder Singh, Vivek Parihar, Sukhpreet singh "Human-AI Collaboration: Understanding User Trust in ChatGPT Conversations" IJSREM, vol. 8 no 1,2024,pp-1-14.
[22] Sikander Hans. Balwinder singh "Enhanced Load Frequency Control in Isolated Micro-Grids Using ANFIS Controller for Stability and Efficiency", International Journal of Applied Science and Technology Research ExcellenceIJSREM, vol. 12 no 6 ,2023, pp-1-18
[23] Saurbh, Ankush, Pankaj, Sikander Hans " Engineering Solutions for Mountainous Road Construction: A Comprehensive Study on Geophysical and Geotechnical Factors Influencing Slope Stability" IJSREM, Vol. 7, no. 12, pp- 1-14.
[24] Balwinder Singh, Sikander Hans "Comparative Study of THD Characteristics in Different Cascaded H-Bridge Configurations for Multilevel Multicarrier Modulation" IJSREM, vol. 8 no 2,2024, pp-1-21.
[25] Bhatt Mishra, D., Naqvi, S., Gunasekaran, A., & Dutta, V. (2023). Prescriptive analytics applications in sustainable operations research: conceptual framework and future research challenges. Annals of Operations Research, 1-40.
[26] Saghafian, S., Austin, G., & Traub, S. J. (2015). Operations research/management contributions to emergency department patient flow optimization: Review and research prospects. IIE Transactions on Healthcare Systems Engineering, 5(2), 101-123.
[27] Bengio, Y., Lodi, A., & Prouvost, A. (2021). Machine learning for combinatorial optimization: a methodological tour d'horizon. European Journal of Operational Research, 290(2), 405-421.
[28] Conejo, A. J., Castillo, E., Minguez, R., & Garcia-Bertrand, R. (2006). Decomposition techniques in mathematical programming: engineering and science applications. Springer Science & Business Media.

[29] Doumpos, M., Zopounidis, C., Gounopoulos, D., Platanakis, E., & Zhang, W. (2023). Operational research and artificial intelligence methods in banking. European Journal of Operational Research, 306(1), 1-16.
[30] Ramezani, A., Khatami Frouzabadi, S. M. A., & Amiri, M. (2023). A review of methods for estimating coefficients of objective functions and constraints in mathematical programming models. International Journal of Nonlinear Analysis and Applications.